We claim:

1. A method for classifying cardiography data, comprising the step of:
applying a kernel transform to sensed data acquired from sensors sensing electromagnetic heart activity, resulting in transformed data, prior to classifying said transformed data using machine learning.

2. The method of claim 1, further comprising the step of:
converting said sensed data into a wavelet domain using a wavelet transform, prior to applying said kernel transform.

3. The method of claim 1, for classifying magneto-cardiography data, further comprising the step of:
acquiring said sensed data from magnetic sensors proximate a patient's heart.

4. The method of claim 2, for classifying of magneto-cardiography data, further comprising the step of:
acquiring said sensed data from magnetic sensors proximate a patient's heart.

5. The method of claim 1, further comprising the step of:
classifying said transformed data using machine learning.

6. The method of claim 2, further comprising the step of:
classifying said transformed data using machine learning.

7. The method of claim 3, further comprising the step of:
classifying said transformed data using machine learning.

8. The method of claim 4, further comprising the step of:
classifying said transformed data using machine learning.

9. The method of claim 1, said kernel transform satisfying Mercer conditions.

10. The method of claim 1, said kernel transform comprising a radial basis function.

11. The method of claim 1, said step of applying a kernel transform comprising the steps of:
assigning said transformed data to a first hidden layer of a neural network;
applying training data descriptors as weights of said first hidden layer of said neural network; and
calculating weights of a second hidden layer of said neural network numerically.

12. The method of claim 11, said step of calculating said weights of said second hidden layer numerically further comprising the step of:
calculating said weights of said second hidden layer using kernel ridge regression.

13. The method of claim 1, said step of applying a kernel transform comprising the step of:
applying a direct kernel transform.

14. The method of claim 1, further comprising the step of:
classifying said transformed data using a self-organizing map (SOM).

15. The method of claim 1, further comprising the step of:
classifying said transformed data using a direct kernel self-organizing map (DK-SOM).

16. The method of claim 1, further comprising the step of:
classifying said transformed data using kernel partial least square (K-PLS) machine learning.

17. The method of claim 1, further comprising the step of:
classifying said transformed data using direct kernel partial least square (DK-PLS) machine learning.

18. The method of claim 1, further comprising the step of:
classifying said transformed data using a least-squares support vector machine (LS-SVM).

19. The method of claim 1, further comprising the step of:
classifying said transformed data using a direct kernel principal component analysis (DK-PCA).

20. The method of claim 1, further comprising the step of:

classifying said transformed data using a support vector machine (SVM / SVMLib).

21. The method of claim 20, said step of classifying said transformed data using a support vector machine (SVM / SVMLib) further comprising the step of:

setting an SVMLib regularization parameter, C, to C=1/λ, for an n data kernel, wherein:

said λ is proportional to said n to a power of 3/2

22. The method of claim 20, said step of classifying said transformed data using a support vector machine (SVM / SVMLib) further comprising the step of:

setting an SVMLib regularization parameter, C, to C=1/λ, for an n data kernel, wherein:

$$\lambda = \min\left\{1;\ \left(\frac{n}{1500}\right)^{\frac{3}{2}}\right\}.$$

23. The method of claim 2, said step of converting said sensed data into a wavelet domain comprising the step of:

applying a Daubechies wavelet transform to said sensed data.

24. The method of claim 2, further comprising the step of:

selecting features from said wavelet data which improve said classification of cardiography data.

25. The method of claim 24, said step of selecting said features further comprising the step of:

eliminating selected undesirable features from said wavelet data.

26. The method of claim 25, said step of eliminating selected undesirable features comprising the step of:

eliminating outlying data from said wavelet data.

27. The method of claim 25, said step of eliminating selected undesirable features comprising the step of:

eliminating cousin descriptors from said wavelet data.

28. The method of claim 24, said step of selecting said features further comprising the step of:

retaining only selected desirable features from said wavelet data.

29. The method of claim 28, said step of retaining only selected desirable features further comprising the steps of:

using a training data set; and

using a validation data set for confirming an absence of over-training of said training set.

30. The method of claim 29, said step of retaining only selected desirable features further comprising the steps\ of:

using a genetic algorithm to obtain an optimal subset of features from said training data set; and

using said genetic algorithm for evaluating performance on said validation date set.

31. The method of claim 29, said step of retaining only selected desirable features further comprising the steps\ of:

measuring sensitivities of said features from said wavelet data in relation to a predicted responses of said features; and

eliminating lower-sensitivity features from among said features with comparatively lower sensitivity than other, higher-sensitivity features from among said features.

32. The method of claim 24, said step of selecting said features further comprising the steps of:

eliminating selected undesirable features from said wavelet data; and

retaining only selected desirable features from said wavelet data.

33. The method of claim 1, further comprising the step of:
normalizing said sensed data.

34. The method of claim 33, said step of normalizing said sensed data comprising the step of:
Mahalanobis scaling said sensed data.

35. The method of claim 1, further comprising the step of:
centering a kernel of said kernel transform.

36. The method of claim 35, said step of centering said kernel comprising the steps of:
subtracting a column average from each column of a training data kernel;
storing said column average for later recall, when centering a test data kernel.
subtracting a row average form each row of said training data kernel.

37. The method of claim 36, said step of centering said kernel further comprising the steps of:
adding said stored column average to each column of said test data kernel;
for each row, calculating an average of said test data kernel; and
subtracting said row average from each horizontal entry of said test data kernel.

38. An apparatus for classifying cardiography data, comprising computerized storage, processing and programming for :
applying a kernel transform to sensed data acquired from sensors sensing electromagnetic heart activity, resulting in transformed data, prior to classifying said transformed data using machine learning.

39. The apparatus of claim 38, further comprising computerized storage, processing and programming for:
converting said sensed data into a wavelet domain using a wavelet transform, prior to applying said kernel transform.

40. The apparatus of claim 38, for classifying magneto-cardiography data, further comprising an input for:
acquiring said sensed data from magnetic sensors proximate a patient's heart.

41. The apparatus of claim 39, for classifying of magneto-cardiography data, further comprising an input for:
acquiring said sensed data from magnetic sensors proximate a patient's heart.

42. The apparatus of claim 38, further comprising computerized storage, processing and programming for:
classifying said transformed data using machine learning.

43. The apparatus of claim 39, further comprising computerized storage, processing and programming for:
classifying said transformed data using machine learning.

44. The apparatus of claim 40, further comprising computerized storage, processing and programming for:
classifying said transformed data using machine learning.

45. The apparatus of claim 41, further comprising computerized storage, processing and programming for:
classifying said transformed data using machine learning.

46. The apparatus of claim 38, wherein kernel transform satisfies Mercer conditions.

47. The apparatus of claim 38, said kernel transform comprising a radial basis function.

48. The apparatus of claim 38, said computerized storage, processing and programming for applying a kernel transform further comprising computerized storage, processing and programming for:
assigning said transformed data to a first hidden layer of a neural network;
applying training data descriptors as weights of said first hidden layer of said neural network; and
calculating weights of a second hidden layer of said neural network numerically.

49. The apparatus of claim 48, said computerized storage, processing and programming for calculating said weights of said second hidden layer numerically further comprising computerized storage, processing and programming for:

calculating said weights of said second hidden layer using kernel ridge regression.

50. The apparatus of claim 38, said computerized storage, processing and programming for applying a kernel transform further comprising computerized storage, processing and programming for:

applying a direct kernel transform.

51. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

classifying said transformed data using a self-organizing map (SOM).

52. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

classifying said transformed data using a direct kernel self-organizing map (DK-SOM).

53. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

classifying said transformed data using kernel partial least square (K-PLS) machine learning.

54. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

classifying said transformed data using direct kernel partial least square (DK-PLS) machine learning.

55. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

classifying said transformed data using a least-squares support vector machine (LS-SVM).

56. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

classifying said transformed data using a direct kernel principal component analysis (DK-PCA).

57. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

classifying said transformed data using a support vector machine (SVM / SVMLib).

58. The apparatus of claim 57, said computerized storage, processing and programming for classifying said transformed data using a support vector machine (SVM / SVMLib) transform further comprising computerized storage, processing and programming for:

setting an SVMLib regularization parameter, C, to $C=1/\lambda$, for an n data kernel, wherein:

said λ is proportional to said n to a power of 3/2

59. The apparatus of claim 57, said computerized storage, processing and programming for classifying said transformed data using a support vector machine (SVM / SVMLib) transform further comprising computerized storage, processing and programming for:

setting an SVMLib regularization parameter, C, to $C=1/\lambda$, for an n data kernel, wherein:

$$\lambda = \min\left\{1;\ \left(\frac{n}{1500}\right)^{\frac{3}{2}}\right\}.$$

60. The apparatus of claim 39, said computerized storage, processing and programming for converting said sensed data into a wavelet domain comprising computerized storage, processing and programming for:

applying a Daubechies wavelet transform to said sensed data.

61. The apparatus of claim 39, further computerized storage, processing and programming for:

selecting features from said wavelet data which improve said classification of cardiography data.

62. The apparatus of claim 61, said comprising computerized storage, processing and programming for selecting said features further comprising computerized storage, processing and programming for:

eliminating selected undesirable features from said wavelet data.

63. The apparatus of claim 62, said comprising computerized storage, processing and programming for eliminating selected undesirable features comprising computerized storage, processing and programming for:

eliminating outlying data from said wavelet data.

64. The apparatus of claim 62, said computerized storage, processing and programming for eliminating selected undesirable features comprising computerized storage, processing and programming for:

eliminating cousin descriptors from said wavelet data.

65. The apparatus of claim 61, said computerized storage, processing and programming for selecting said features further comprising computerized storage, processing and programming for:

retaining only selected desirable features from said wavelet data.

66. The apparatus of claim 65, said computerized storage, processing and programming for retaining only selected desirable features further comprising computerized storage, processing and programming for:

using a training data set; and

using a validation data set for confirming an absence of over-training of said training set.

67. The apparatus of claim 66, said computerized storage, processing and programming for retaining only selected desirable features further comprising computerized storage, processing and programming for:

using a genetic algorithm to obtain an optimal subset of features from said training data set; and

using said genetic algorithm for evaluating performance on said validation date set.

68. The apparatus of claim 66, said computerized storage, processing and programming for retaining only selected desirable features further comprising computerized storage, processing and programming for:

measuring sensitivities of said features from said wavelet data in relation to a predicted responses of said features; and

eliminating lower-sensitivity features from among said features with comparatively lower sensitivity than other, higher-sensitivity features from among said features.

69. The apparatus of claim 61, said computerized storage, processing and programming for selecting said features further comprising computerized storage, processing and programming for:

eliminating selected undesirable features from said wavelet data; and

retaining only selected desirable features from said wavelet data..

70. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

normalizing said sensed data.

71. The apparatus of claim 70, said computerized storage, processing and programming for normalizing said sensed data comprising computerized storage, processing and programming for:

Mahalanobis scaling said sensed data.

72. The apparatus of claim 38, further comprising computerized storage, processing and programming for:

centering a kernel of said kernel transform.

73. The apparatus of claim 72, said computerized storage, processing and programming for centering said kernel comprising computerized storage, processing and programming for:

subtracting a column average from each column of a training data kernel;

storing said column average for later recall, when centering a test data kernel.

subtracting a row average form each row of said training data kernel.

74. The apparatus of claim 73, said computerized storage, processing and programming for centering said kernel further comprising computerized storage, processing and programming for:

adding said stored column average to each column of said test data kernel;

for each row, calculating an average of said test data kernel; and subtracting said row average from each horizontal entry of said test data kernel.